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COMPUTERIZED INTERPRETATION OF ERTS DATA FOR FOREST MANAGEMENT

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Managers of forest resources are faced with increasing demands for forest products as well as the needs of alternative uses for the land surface. Consideration must be given to the environmental problems associated with the removal of forest by harvesting, diseases or pests, and the effects of forest removal on the ever-increasing needs for pure water.

ERTS-A data have opened up many possibilities for effective management. However, new processing and analysis techniques are required to exploit these data. In particular, automatic data processing appears mandatory for many interpretation and inventory functions. For example, automatic stratification by type and density class provides a common basis for multiple uses. The data can be formatted for convenient insertion into a computerized data bank. Processing of repetitive coverages increases the accuracy of the inventory data and detects changes and trends.

One of the study areas used for automatic classification of forested areas was the Cloquet, Minnesota area, located 25 miles west of Duluth. Approximately 24,000 acres of forest and associated land use types were stratified. The features used for classification were derived from the four MSS bands of ERTS-A image 1075-16312, an October 6, 1972 coverage of the Cloquet study area. Data was extracted from the 7-track 800 BPI computer compatible tapes (CCT). Ground truth information was obtained by using aerial photointerpreters from the University of Minnesota's Institute of Agriculture Remote Sensing Laboratory (IARSL), located in the College of Forestry. Since the College's Cloquet Forestry Center, an experimental forest, is in the midst of this area, much information was previously known about the forest types. Spring 1:90,000 panchromatic aerial photographs, numerous field checks, and previous ground experience in the study area were used by the interpreters in generating the ground truth map. The Cloquet area was delineated into five classes: conifers, hardwoods, open, water and urban.

Having determined that land use classes can be delineated with reasonable accuracy on the Cloquet test site, i.e., that forested areas can be isolated from other land uses, the Chippewa National Forest was selected as a second test site for determining the feasibility of delineating forest types. The Chippewa National Forest contains 1.3 million acres with a broad spectrum of tree species. It contains approximately equal amounts of hardwoods and conifers and is a management unit to which automatic classification results may be applied. The Chippewa National Forest was covered by a NASA RB-57 overflight providing additional ground truth information at 1:60,000. Approximately 200,000 acres have been delineated by a trained photointerpreter familiar with the area. Twelve forest types were delineated, namely: hardwood, conifer, and mixed (containing more than 25% of both varieties); these three types are further delineated into upland or lowland and finally into high and low crown density (above or below 50%). Features were derived from two cloud-free ERTS digital tapes 1076-16370, an October 7th coverage and 116-16373, a January 5th coverage. The species included in the broad cover types are listed below:

	Upland	Transition	Lowland
Conifer	Jack pine Red pine White spruce White pine	Balsam fir	Black spruce Tamarack Northern white cedar
Hardwood	Trembling aspen Paper birch American basswood Sugar maple Big tooth aspen Red oak	Green ash American elm Yellow birch	Black ash Balsam poplar Silver maple

Two types of features were used for automatic classification, namely: multi-spectral and spatial. The multi-spectral data consisted of the output of the four MSS bands sensitive to .5-.6, .6-.7, .7-.8, and .8 to 1.1 microns. When seasonal coverage was used (e.g., over the Chippewa National Forest), the multi-spectral feature vector consisted of the four bands from each coverage. Only the most effective features were retained according to their effectiveness for class separation. To increase the amount of information contained in the feature set and improve classification accuracy, spatial features were added. An evaluation of three spatial frequency algorithms was made, the Fourier, Walsh and Slant transforms.

Edges in a picture introduce spatial frequencies along a line in the complex frequency plane orthogonal to the edge. High spatial frequencies correspond to sharp edges and low spatial frequencies correspond to regions of approximately uniform grey land. Spatial filtering in an image to detect the texture is a natural extension to two dimensions of the traditional one-dimensional or temporal filtering process in communication networks. The Fourier transform is a tool for computing the frequency components of a temporal waveform. The orthogonal basis functions are sinusoidal. Digital implementation of the Fourier transform became feasible for two dimensions with the development by Cooley and Tukey of the Fast Fourier transform (FFT). The FFT was our first algorithm used to generate spatial features. Although it is inferior to the Karhunen Loeve transform in a mean square error sense, it can be computed far more efficiently with $N \log_2 N$ computer operations where N is the dimensionality of the pattern space.

The second algorithm used to measure spatial frequency was the Walsh Hadamard transform. This transformation has a number of advantages; it can be derived with $N \log_2 N$ additions or subtractions and is binary so that it is amenable to digital computation. Sequency is proportional to the number of zero crossings of the Walsh wave; the analogy with the sinusoidal frequency descriptor is obvious.

The third algorithm used for spatial features is the Slant transform. Pratt, et al., from the University of Southern California developed a computationally fast Slant algorithm. One of the advantages of the Slant transform is the compaction of the image energy into a minimum number of basis vectors which resemble typical horizontal or vertical lines of an image. Generally lines in an image will have a constant grey level, over considerable length or linearly vary in brightness over the length. The orthogonal set of basis functions in the Slant transform tend to accommodate this type of data. It also has a sequency property descriptive of frequency content. Some of the basis vectors of the Slant transform are identical to the Walsh basis vectors. Pratt has shown that the mean square error between an image and the Slant transform is almost as small as that of the Karhunen Loeve transform.

Once the feature vector was selected, the training and testing samples for an automatic classifier were extracted from the digital tape as follows: The ERTS computer compatible tapes were reproduced on film by writing with a digital magnetic tape to film printer for purposes of registering with ground truth information. The output film provides an image of the study area containing grid lines corresponding to record and word on the digital magnetic data tape. Registration of ground truth with ERTS-A data from band 7 was accomplished by recognition of landmarks such as the numerous water bodies in the area. Once ground truth and ERTS-A data were registered, type boundaries were encoded in terms of record and word numbers. From within the type boundaries, data arrays were isolated to serve as training samples. The size of the arrays was varied starting with an 8 x 8 array or 70 ground acres. As the array size increases, the feature set is better able to describe the original image and therefore the classification accuracy increases. However, the larger array size decreases ground resolution.

Having selected the features to be used and the training set, a linear discriminant classifier is trained. Briefly, the classifier algorithm which we call K-class groups each of the features of the training set around an orthogonal basis vector in a least mean square sense. The matrix required to do this is computed for subsequent application to the input data during testing and during the generation of overlay maps. The class to which the input data point belongs is determined by the distance from the various orthogonal vector points.

Because the mapping errors and the distributions of the various classes are different, it would be a coincidence that the linear boundaries between classes determined by the K-class algorithm would be optimum when all the classes are weighted alike. Thus, we find it advantageous to adjust the weights of each class to minimize the total mapping error. This adjustment does not actually minimize the mapping error, but does minimize the number of mistakes in the training set of samples, which is surely directly proportional to the mapping error. In addition, a cost parameter is included which will "guard" one class over another.

Initially, all weights are set equal and the coefficient matrix is computed and used to test the training set of samples. Based on the testing results, the class weights are adjusted and the new coefficient matrix is tested. This is continued while the step size is varied until the step size is 0. Any time the testing results are worse than a previous best, the step size is reduced by a factor δ.

A by-product of the K-class algorithm is a distance formula which measures the statistical distance between classes. This formula is much like the well-known Divergence measure. The only difference between the two is that the Divergence measure is based on the likelihood ratio algorithm, while the K-class distance is based on the K-class algorithm. The two measures can be derived using the same logical steps. The K-class program prints out the distance between classes and the component of that distance attributed to feature k. Thus features are ranked according to efficacy for separating classes and the least effective features can be deleted.

Using only multi-spectral features, the classifier was trained on data derived from each class on the Cloquet test site. The total training area was approximately 5000 acres proportioned into five classes. When testing on the same data, seventy-four percent of the data are correctly classified. When adding texture computed on an 8 x 8 array, the classification accuracy increased to 99%.

In comparing the texture algorithms, it was found that the Slant transform provides the highest classification accuracy. For arrays 8 x 8 and smaller, the Walsh transform outperforms the Fast Fourier. As the dimensionality is increased, the Fourier transform performance should be better than either the Walsh or Slant transforms since the Fourier transform is asymptotically equivalent to the Karhunen Loeve transform.

Stratification information is useful to natural resource land managers. Our goal is to determine the capabilities of automatic classification from ERTS-A data, the maximum number of classes and an acceptable operational data format. In addition, we seek to determine the best combination of automatic and human interpretation. We will compare automatic techniques to studies being done by IARSL on the Chippewa National Forest and the State of Minnesota Land Management Information System.